Synopsis on

Satellite Imagery Segmentation and Classification Techniques

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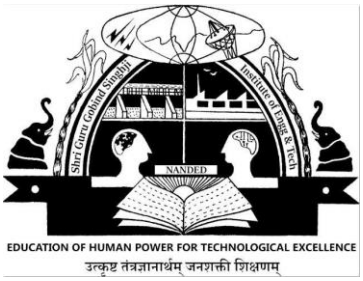

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Satellite Imagery Segmentation and Classification Techniques

A satellite image is an image of the whole or part of the earth taken using artificial satellites. These images have a variety of uses, including: cartography, military intelligence and meteorology. Satellite images can either be visible light images, water vapor images or infrared images. Satellite images are like maps: they are full of useful and interesting information. They can show us how much a city has changed, how well our crops are growing, where a fire is burning, or when a storm is coming.

Satellite images are one of the most powerful and important tools used by the meteorologist. They are essentially the eyes in the sky. These images reassure forecasters about behavior of the atmosphere as they give a clear, concise, and accurate representation of how events are unfolding. Forecasting the weather and conducting research would be extremely difficult without satellites. Satellite images are mainly used in geographic information systems (GIS). Their classification is very useful for cartography.

Satellite images have many applications in meteorology, oceanography, fishing, agriculture, biodiversity conservation, forestry, landscape, geology, cartography, regional planning, education, intelligence and warfare. Images can be in visible colors and in other spectra. There are also elevation maps, usually made by radar images. Interpretation and analysis of satellite imagery is conducted using specialized remote sensing applications.

There are two types of satellites that orbit the Earth, polar and geostationary. Geostationary Operational Environmental Satellites (GOES) remain above a fixed location on the Earth's surface, approximately 22,500 km above the equator. Because the satellites rotate with the Earth, they always view the same portion of the globe. The polar orbiting satellites, in contrast, orbit at much lower elevations (800-900 km). Their path is 2,400 km wide centered at the orbit path. The polar satellites observe a new path on each orbit. Polar satellites are not as useful to operational meteorologists because they do not continuously view the same area. Geostationary satellites allow meteorologists to view the weather as it develops since they view the same area continuously.

Commercial satellites have a spatial resolution down to 50 centimeters per pixel. The most detailed NASA images show 10 meters in each pixel. Geostationary weather satellites, which observe a whole hemisphere at a time, are much less detailed, seeing one to four kilometers in a pixel.

Applications of Remote Sensing Technology-

Some of the areas in which satellite remote sensing technology has been applied with varying degree of impact are as follows:

• Natural Resources (Agriculture mapping, Forestry, Soil moisture and Ocean Salinity)

• Defense and Security (Crime mapping, Homeland Security)

• Environmental Management (Disaster monitoring and mitigation, Global Climate change, Conservation, Land cover and change detection, Natural Hazards)

• Surveying and urban planning

• Water resource management

• Environmental monitoring

• National spatial data infrastructure

• Engineering and Construction (3D Urban and Terrain modelling, Airport Mapping DB, Urban and Land development)

• Energy (Mineral, Oil and Gas exploration)

• Telecommunication

• Coastal eco-system monitoring

Resolution in satellite imagery and Data-

There are four types of resolution when discussing satellite imagery in remote sensing: spatial, spectral, temporal, and radiometric. Campbell (2002) defines these as follows:

Spatial resolution is defined as the pixel size of an image representing the size of the surface area (i.e. m^2) being measured on the ground, determined by the sensors' instantaneous field of view (IFOV);

Spectral resolution is defined by the wavelength interval size (discrete segment of the Electromagnetic Spectrum) and number of intervals that the sensor is measuring;

Temporal resolution is defined by the amount of time (e.g. days) that passes between imagery collection periods for a given surface location

Radiometric resolution is defined as the ability of an imaging system to record many levels of brightness (contrast for example) and to the effective bit-depth of the sensor (number of grayscale levels) and is typically expressed as 8-bit (0-255), 11-bit (0-2047), 12-bit (0-4095) or 16-bit (0-65,535).

Geometric resolution refers to the satellite sensor's ability to effectively image a portion of the Earth's surface in a single pixel and is typically expressed in terms of Ground sample distance, or GSD. GSD is a term containing the overall optical and systemic noise sources and is useful for comparing how well one sensor can "see" an object on the ground within a single pixel.

Imaging Satellites

GeoEye - GeoEye's GeoEye-1 satellite was launched September 6, 2008. The GeoEye-1 satellite has the high resolution imaging system and is able to collect images with a ground resolution of 0.41 meters (16 inches) in the panchromatic or black and white mode. It collects multispectral or color imagery at 1.65-meter resolution or about 64 inches.

DigitalGlobe - DigitalGlobe's WorldView-2 satellite provides high resolution commercial satellite imagery with 0.46 m spatial resolution (panchromatic only). The 0.46 meters resolution

of WorldView-2's panchromatic images allows the satellite to distinguish between objects on the ground that are at least 46 cm apart. Similarly DigitalGlobe's QuickBird satellite provides 0.6 meter resolution (at NADIR) panchromatic images.

ASTER - The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is an imaging instrument onboard Terra, the flagship satellite of NASA's Earth Observing System (EOS) launched in December 1999. ASTER is a cooperative effort between NASA, Japan's Ministry of Economy, Trade and Industry (METI), and Japan Space Systems (J-spacesystems). ASTER data is used to create detailed maps of land surface temperature, reflectance, and elevation. The goal of NASA Earth Science is to develop a scientific understanding of the Earth as an integrated system, its response to change, and to better predict variability and trends in climate, weather, and natural hazards.

Segmentation and Classification in Satellite Imagery

Several algorithms are available that perform the task of effective classification by combining two different steps: segmentation and classification. In the first step, the aim is to divide the image into homogenous regions. No labels are attributed, this is only a preprocessing. In the second step, features such as intensity, texture or shape are extracted from these regions in order to perform a region-based classification. At the end of this step a label is attributed to each region, corresponding to the final classification.

What is Image Segmentation in Remote Sensing?

The segmentation step is generally made up of three parts. We first have the pre-processing, in which we select the features to use and eventually modify or re-scale the data. The second part is the initialization of the segmentation algorithm, if needed. Finally the third part is the segmentation itself. The aim of the proposed work here is to show which method and which features provide the best segmentation?

The effectiveness of the segmentation depends on the preprocessing. Moreover, if it is not properly performed, the segmentation may fail. This pre-processing is made up of two parts: feature selection and re-scaling methods.

A) Pre-processing

i) Feature selection Methods generally used are state-of-the-art pixel Intensity, Gray level co-occurrence matrix, energy filters, Gabor filters, Wavelet decomposition. Most of satellite or aerial images are multi-spectral, we then have several bands that we can use for the segmentation. Although the information between the bands are strongly correlated, especially between blue, green and red, the more the bands, the best the segmentation results.

ii) Re-scaling Methods generally used are clustering, PCA, logarithm, etc. In order to ensure the effectiveness of the segmentation step we the logarithm pre-processing is used whenever the distribution of intensity in a band is too sparse. The number of bands could be decreased by using the principal component analysis, but the results are sometimes slightly worse. If the computing time is critical or if the number of bands is too high, this is an effective method to reduce the amount of data.

B) Segmentation Algorithms Various algorithms that can be applied to single band include Split and merge, Watershed, K-means, Finite Gaussian Mixture Model (FGMM) and Markov models.

What is Image Classification in Remote Sensing?

The basic principle of the classification is to assign a label to each instance, which is for remote sensing images either a pixel or a region. Each label corresponds to a class having its own properties. The algorithm that assigns these labels is called classifier. The classifier, which can be supervised or not, uses extracted features from the data to choose the labels.

The classification step is then made up of three parts. In the first part, several features like intensity, texture and shape are extracted from the created regions. Then the second part consists of selecting the most appropriate and relevant features using cross-validation or sequential generation. Finally, the classification is performed using any of the numerous classifiers like SVM, K-means, FGMM, Mahalonobis distance, KNN, Neural Network, etc.

In general, the three main image classification techniques in remote sensing are:

1. Unsupervised image classification

2. Supervised image classification

3. Object-based image analysis

Unsupervised and supervised image classification techniques are the two most common approaches. However, object-based classification has been used more lately because of it's usefulness for high-resolution data.

Unsupervised Classification

In unsupervised classification, it first groups pixels into "clusters" based on their properties. In order to create "clusters", analysts use image clustering algorithms such as K-means and ISODATA. After picking a clustering algorithm, you identify the number of groups you want to generate. For example, you can create 8, 20 or 42 clusters. For example, if you want to classify cultivated and non-cultivated land, you'll have to merge clusters into only 2 clusters.

Overall, unsupervised classification is the most basic technique. Because you don't need samples for unsupervised classification, it's an easy way to segment and understand an image.

Supervised Classification

In supervised classification, you select representative samples for each land cover class. The algorithm then uses these "training samples" and applies them to the entire image.

Supervised classification uses the spectral signature defined in the training set. For example, it determines each class on what it resembles most in the training set. The common supervised classification algorithms are maximum likelihood and minimum-distance classification.

Object-Based (or Object-Oriented) Image Analysis Classification

Supervised and unsupervised classification is pixel-based. In other words, it creates square pixels and each pixel has a class. But object-based image classification groups pixels into representative shapes and sizes. This process is multi-resolution segmentation or segment mean shift.

Multiresolution segmentation produces homogenous image objects by grouping pixels. It generates objects with different scales in an image simultaneously. These objects are more meaningful because they represent features in the image. But most importantly, you can classify objects based on texture, context and geometry.

In OBIA, you can use multiple bands to create objects and then classify them. For example, OBIA can take infrared, elevation or a shapefile to classify each object. Also, layers can have context with each other. For example, objects have proximity and distance relationships between neighbors.

Selection of Image Classification Techniques

When should you use pixel-based (unsupervised and supervised classification)? When should you use object-based classification? Spatial resolution is an important factor when selecting image classification techniques.

When you have low spatial resolution, both traditional pixel-based and object-based image classification techniques perform well. But when you have high spatial resolution, OBIA is superior to traditional pixel based classification.

Unsupervised vs Supervised vs Object-Based Classification

A case study from the University of Arkansas compared object-based vs pixel-based classification. The goal was to compare high and medium spatial resolution imagery.

Overall, object-based classification outperformed both unsupervised and supervised pixel-based classification methods. Because OBIA used both spectral and contextual information, it had higher accuracy. This study is a good example of some of the limitations of pixel-based image classification techniques.

Objective of the proposed work

The resolution of images provided by the satellites is increasing every day. Some years ago, these images had a resolution of dozens of meters. The measured luminance of one pixel was representing the mean of luminance of several ground objects. Now the new satellites reach sixty centimeters of resolution, increasing the level of detail by a factor ten. With such images we can consider that each pixel is part of a single object. Thus, the heterogeneity of images has dramatically grown. Satellite images are mainly used in geographic information systems (GIS). Their classification is very useful for cartography. With low resolution satellite images, the intensity of the pixels is enough to individually classify each of them. On the contrary, high resolution image classification is more difficult. The increasing complexity of the scenes raises the level of details.

The improvements of satellite imaging now require new segmentation and classification methods. Some classifiers developed for biomedical imagery or industry are still uncommon in remote sensing. Moreover in biomedical imagery a pre-processing step, the segmentation, is

often added. Its aim is to divide the image into homogenous regions in order to extract contextual features. All these new methods are not fully exploited in remote sensing.

A global process for remote sensing image classification is needed, exceeding the limits of the existing remote sensing classification algorithms. Due to the fact that ground-truth images are difficult to obtain, the robustness of classification process is needed. Some improvements can also be added to existing methods like post-processing could be inserted to suppress the noise in the homogenous regions. The segmentation step could also be improved in order to increase the potential of the classification step. The work here proposes to make use of Deep learning or Machine learning techniques to increase the segmentation and classification accuracy. However, due to the limits imposed by remote sensing acquisition systems the classification process may be affected. Also, the work includes improvements in selection of relevant features, feature dimensionality reduction techniques, detection of relevant textural cues and shapes to enhance the segmentation and classification of satellite images.

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